



Multifidelity DDDAS Methods with Application to a Self-Aware Aerospace Vehicle

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Abstract

A self-aware aerospace vehicle can dynamically adapt the way it performs missions by gathering information about itself and its surroundings and responding intelligently. We consider the specific challenge of an unmanned aerial vehicle that can dynamically and autonomously sense its structural state and re-plan its mission according to its estimated current structural health. The challenge is to achieve each of these tasks in real time—executing online models and exploiting dynamic data streams—while also accounting for uncertainty. Our approach combines information from physics-based models, simulated offline to build a scenario library, together with dynamic sensor data in order to estimate current flight capability. Our physics-based models analyze the system at both the local panel level and the global vehicle level.

Keywords:

1 Introduction

A self-aware aerospace vehicle can dynamically adapt the way it performs missions by gathering information about itself and its surroundings and responding intelligently. Such a vehicle embodies the paradigm of a dynamic data-driven application system (DDDAS), whereby “application (or simulations) and measurements become a symbiotic feedback control system”¹. Making the vision of a self-aware aerospace vehicle a reality requires new DDDAS approaches that drive decision-making through dynamic response to uncertain data, while incorporating information from multiple modeling sources and multiple sensor fidelities. We consider the specific challenge of an unmanned aerial vehicle (UAV) that can dynamically and autonomously sense, plan, and act. The challenge is to achieve these tasks in real time—executing online models and exploiting dynamic data streams—while also accounting for uncertainty. Our advances

¹<http://www.dddas.org/>

will enable a revolutionary new generation of self-aware UAVs that can perform missions that are impossible using current design, flight, and mission planning paradigms.

Figure 1 shows our approach that combines offline computation with online sensor data to provide a time-constrained, updated estimate of UAV flight capability. More specifically, we combine information from physics-based models, simulated offline to build a scenario library, together with dynamic sensor data in order to estimate current flight capability. We also use dynamic data to modify our information-gathering strategies to manage uncertainty in our capability estimates.

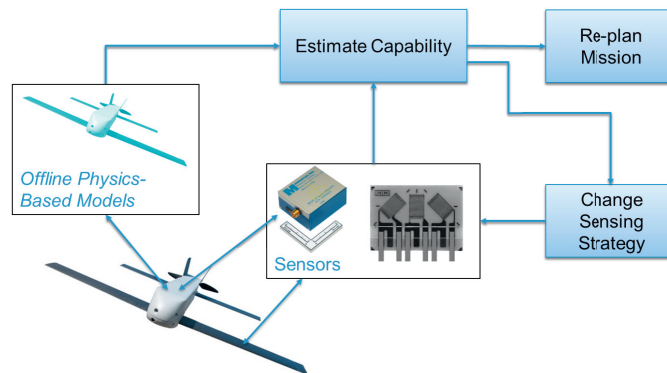


Figure 1: To achieve a self-aware vehicle capability, we use offline physics-based modeling combined with dynamic sensor data to achieve dynamically updated estimates of vehicle capabilities (e.g., the vehicle flight envelope).

Significant recent advances have greatly increased the capabilities of structural sensing and vehicle health monitoring systems. Operational loads monitoring uses on-board aircraft sensors to identify damage and fatigue, with a goal of reducing maintenance costs and increasing reliability [1]. Integrated vehicle health management systems combine operational data, physics-based models, and prognosis techniques to detect damage, fatigue and loss of aircraft capability [2, 3, 4]. The digital twin paradigm takes this vision even further, aiming to achieve data-informed vehicle certification and sustainment [5]. The advent of increased on-board data availability together with increased on-board computing power offers an opportunity to extend the digital twin paradigm even further to support real-time and on-board decision-making. To achieve this requires DDDAS modeling approaches and algorithms.

One example of real-time integration of data and modeling is the On-Board Active System Safety (ONBASS) project, which aims to achieve real-time aircraft health monitoring and on-board risk analysis [6]. As another example, Ref. [7] develops a DDDAS approach for real-time monitoring of stochastic damage, using high-fidelity models to create candidate models of system behavior that are then weighted based on real-time data. Real-time assessment results in actions to increase estimation confidence as well as actions to heal the system given current damage estimates. Our approach parallels the offline/online strategy of [7], but we focus on the mapping from sensed data to system capability (in our case the updated vehicle flight envelope) rather than attempting to infer damage state.

2 Approach

We describe the problem setup and then present the offline and online elements of our approach.

2.1 Problem setup

We consider two kinds of quantities of interest:

- The quantities that are measured during flight, referred to as the *measured quantities of interest*. We denote these by $\mathbf{q}_m(\mathbf{x})$, $m = 1, \dots, M$, where \mathbf{q}_m is the m th measured quantity of interest (generally a vector representing a discretized field quantity) and we consider M such quantities.
- The quantities employed in the decision process that give information about capability and performance constraints, referred to as the *capability quantities of interest*. We denote these by $\mathbf{s}_c(\mathbf{x})$, $c = 1, \dots, C$, where \mathbf{s}_c is the c th capability quantity of interest (generally a vector representing a discretized field quantity) and we consider C such quantities.

Both quantities of interest are functions of the vehicle state, \mathbf{x} , which includes quantities describing the current damage state (e.g., damage location, extent and depth). In an offline phase, we use high-fidelity models to obtain detailed information about the system and its possible responses for different flight conditions and different damage states. The simulated information is stored in a damage library and is used to build a mapping from measured quantities of interest to capability quantities of interest via surrogate models. In the online phase, these surrogate models provide rapid estimates of vehicle capability given real-time measurements. The next two subsections describe in more detail the models and methods employed in our offline and online phases.

2.2 Offline stage

Our offline phase considers a suite of multifidelity physics-based models, at varying levels of physics resolution, and ranging from the panel level to the full vehicle level. We store offline analysis information in a damage library. We use a variety of strategies to build surrogate models from this information, including support vector machines, proper orthogonal decomposition (POD) and self-organizing maps.

Vehicle-level models. At the vehicle level, a combination of ASWING [8] and the Variational Asymptotic Beam Cross-Sectional Analysis (VABS) [9] provides estimates of internal wing stresses and deflections as a function of input aircraft kinematic states and estimates of damage to the nominal aircraft structure.

ASWING [8] is a nonlinear aero-structural solver for flexible-body aircraft configurations of high to moderate aspect ratio. ASWING uses unsteady lifting line aerodynamics together with a finite difference Euler-Bernoulli beam structural model. The aerodynamic model is extended with Prandtl-Glauert compressibility treatment and a sectional stall model. The nonlinear Euler-Bernoulli beam model permits analysis of large deflections. Figure 2 shows the ASWING representation of our concept UAV and the corresponding aerostructural assessment for an example pull-up maneuver. The ASWING model is a set of interconnected slender beams—one each for the wing, fuselage, horizontal stabilizer, and vertical stabilizer. Lifting surfaces (the wing and stabilizers) have additional cross-sectional lifting properties that are pre-specified.

VABS [9] models the wing box as an array of two-dimensional cross-sectional finite element models. The cross-sections capture the details of a multi-ply composite wing skin and local damage effects. VABS computes lumped stiffness and inertial properties at a reference point in each cross section, forming a global line representation of the beam. A standard beam problem

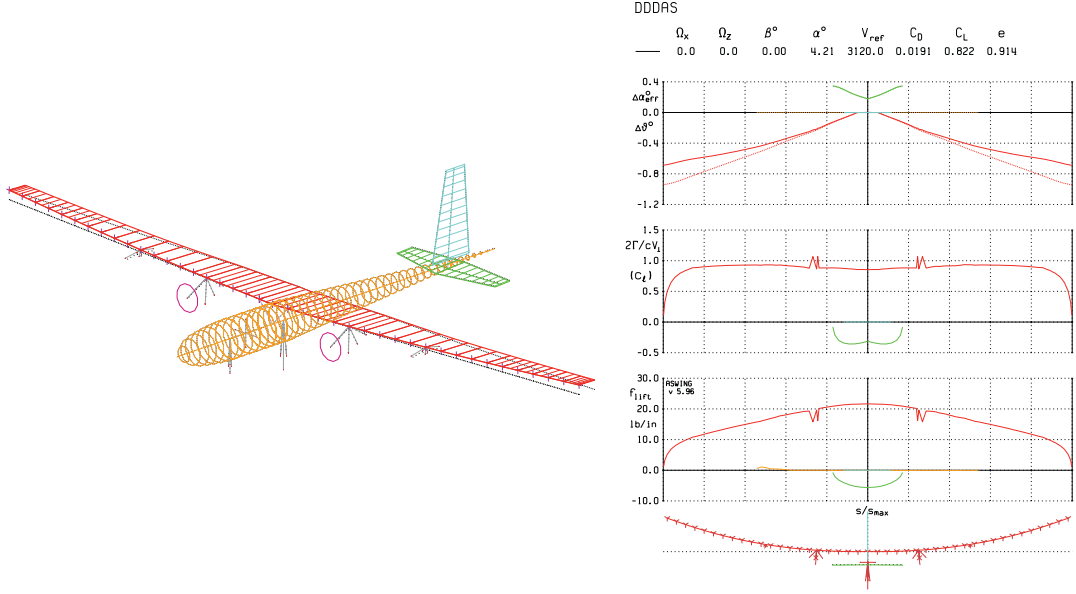


Figure 2: The representation of our concept UAV within ASWING. The structure is specified as a set of interconnected slender beams, where lifting surfaces have additional aerodynamic properties specified along their span. The plots to the right show the aeroelastic trim solution computed by ASWING for a pull-up maneuver at a fixed flight velocity and load factor.

solver finds the global force and moment distribution along this reference line given input forces and moments. Using the reference line solution, the internal strain field can be recovered in the beam cross sections using relations initially computed by VABS. Figure 3 provides an overview of the VABS modeling framework. In this work, we use the specific UM/VABS implementation developed in FORTRAN by R. Palacios and C. Cesnik at the University of Michigan [10].

In our integrated modeling setup, ASWING manages the one-dimensional beam solution, computing loads in the wing box for specific flight conditions, while VABS resolves local stiffness loss due to damage on the aircraft wing.

Panel-level models. At the panel level, we use a finite element model that simulates and analyzes the panel behavior under specified loading and damage scenarios using a plate model. The composite panel comprises carbon fiber plies with a specified stacking sequence. Four clamped edges define boundary conditions that simulate the presence of fastening bolts along the panel perimeter. Figure 4 shows a panel layout and corresponding panel cross-section for a case with four plies with the symmetric stacking sequence $[\pm 45^\circ, 0^\circ/90^\circ, 0^\circ/90^\circ, \pm 45^\circ]$. The border area that hosts the holes is reinforced with two additional plies with orientation $0^\circ/90^\circ$ and $\pm 45^\circ$. The grey shaded area on the right plot of Figure 4 denotes the damaged region, which is centered at (y_d, z_d) and has extent $\Delta y \times \Delta z$.

The loads l on the panel are defined by the prescribed aircraft maneuver. The presence of damage is simulated by weakening the stiffness properties of the finite elements that belong to the prescribed damaged area. This model is used to explore different damage scenarios. For each scenario, we generate a snapshot set by evaluating the measured quantities of interest and the capability quantities of interest. The measurement quantities of interest are the components

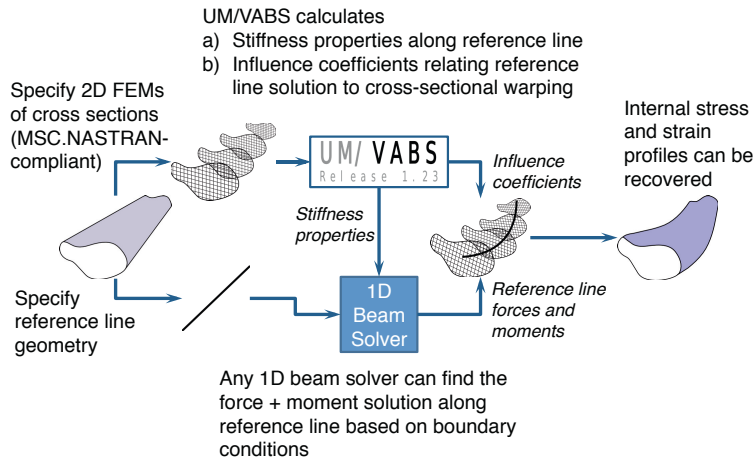


Figure 3: Variational Asymptotic Beam Cross-Sectional Analysis (VABS) allows for dimensional reduction of an expensive three-dimensional beam solution into two-dimensional finite element models coupled with an external beam solver.

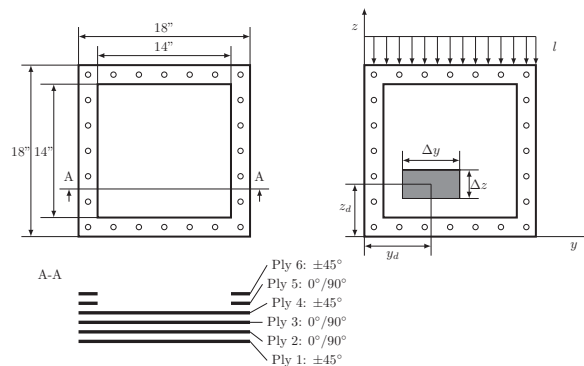


Figure 4: Panel layout and layer sequence. Panel state variables include the damage location, damage size, and load definition.

of strain evaluated for each element in the computational mesh. The capability quantities of interest are the failure indices, also evaluated for each element in the computational mesh. Failure index is an indicator of the structural condition that is translated into a scaling factor for maneuver parameters. It is defined as the ratio between the experienced stress and the maximum allowable stress (typically the compression/tension/shear strength that characterizes the material properties).

Damage library. The purpose of the damage library is to store information from analyses run offline using the panel-level and vehicle-level models. This information may be accessed by online analyses in a variety of different ways (e.g., directly accessing the predictions associated with a damage scenario, or using library entries to perform dynamic adaptation of a reduced-order model). The damage library is populated by offline analysis of a range of damage scenarios

and kinematic states relevant to the planned mission of the vehicle. Information regarding the planned mission can be used to determine the type of damage that may occur and the types of maneuvers that may be performed. This information, along with resource constraints on the library, can be used to optimize the contents of the damage library given mission level objectives. In our current implementation, the library contains model predictions of sensed strain and maximum failure indices for each scenario considered. Ongoing work is investigating the utility of including model predictions of other quantities.

Classification and surrogate modeling. We embody the information generated by these physics-based models using various surrogate modeling techniques. At the panel level, we build low dimensional representations of the measured and capability quantities of interest, using the POD. We then use self-organizing maps to cluster the resulting data and to build a surrogate model that maps measurements to capability estimates. The steps in this process are outlined in Figure 5. The details of the panel-level approach are described in [11].

At the vehicle level, we use the maximum computed failure index to classify all simulated conditions into safe (maximum failure index < 1) and unsafe (maximum failure index ≥ 1). We build a representation of the failure boundary (maximum failure index $= 1$) as a function of damage parameters and vehicle operating conditions. Our current implementation uses a simple bisection method to define the failure boundary; future work will use adaptive sampling with support vector machines as in [12]. The steps in this process are outlined in Figure 6 and are described in more detail in [13].

2.3 Online stage

In the online stage, our goal is to move from sensed data to updated estimates of structure capability at the local panel level and updated flight envelopes at the vehicle level. The key is to achieve these estimates sufficiently rapidly to support dynamic decision-making, while leveraging the rich amount of physics-based information contained within our damage library. We also aim to characterize our level of confidence in our updated estimates.

At the panel level, the low-dimensional POD representations combined with the self-organizing map clustering achieve the desired rapid assessment. Figure 5 shows the online flow of analysis that moves from sensed strain data to estimates of panel failure indices. The reconstruction of the POD coefficients in the second step is achieved using the gappy POD approach [14, 15].

At the vehicle level, we use a Bayes classifier that assigns a posterior estimate of the probability of being in any damage state contained in our damage library. A simple approach, described in [13], assigns equal prior probability to each damage state in the library and classifies the vehicle's damage state as the state in the library with the maximum posterior probability. A more sophisticated approach incorporates mission information, current maneuver, and a mixture model of the posterior damage state. The additional mission and maneuver information permit us to relax the assumption of equal prior damage state probabilities. The mixture model of the posterior damage state enables interpolation among records in the damage library, permitting us to characterize a richer range of vehicle damage states.

3 Results

The offline vehicle model allows for determination of the vehicle capability over a range of damage events using classification. Figure 7 shows an example of this process. We simulate a pull-up maneuver at constant velocity $V = 260$ ft/s with varying load factor $n \in [1, 3.5]$ over a range of two chordwise damage size parameters, with fixed spanwise size parameters and constant depth. Each damage and maneuver combination is classified as “safe” or “unsafe”

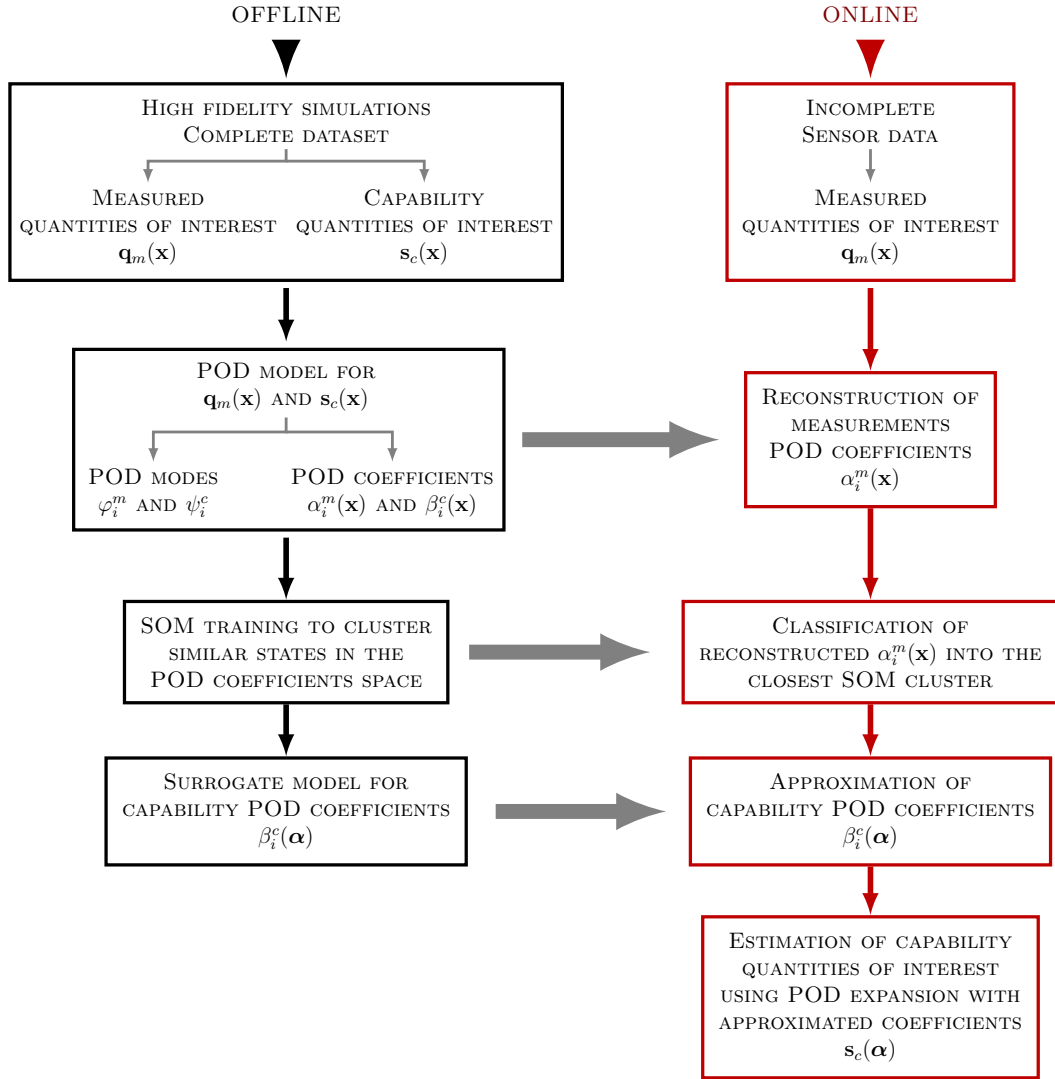


Figure 5: Diagram of the offline (black boxes) and online (red boxes) steps of our approach at the panel level. POD models and clusters are obtained offline and employed online as indicated by the gray arrows.

based on the value of the maximum failure index in the wing structure. Using this classifier variable, the boundary surface between safe and unsafe maneuver regions for any given damage case can be determined using a bisection algorithm.

Figure 8 presents results for an example case at the panel level. The surrogate models are obtained offline using an evaluation set of 3000 different damage cases for fixed panel layout and loading condition (Figure 4). We show here results for the case of a 3.5220×7.7540 square-inch damage located at $(y_d = 10.5900, z_d = 12.9100)$ and involving plies 4, 5 and 6. The figure shows the original finite element solution for the failure index field over the panel. We use this solution to generate synthetic data with which to test our approach. The bottom right plot of

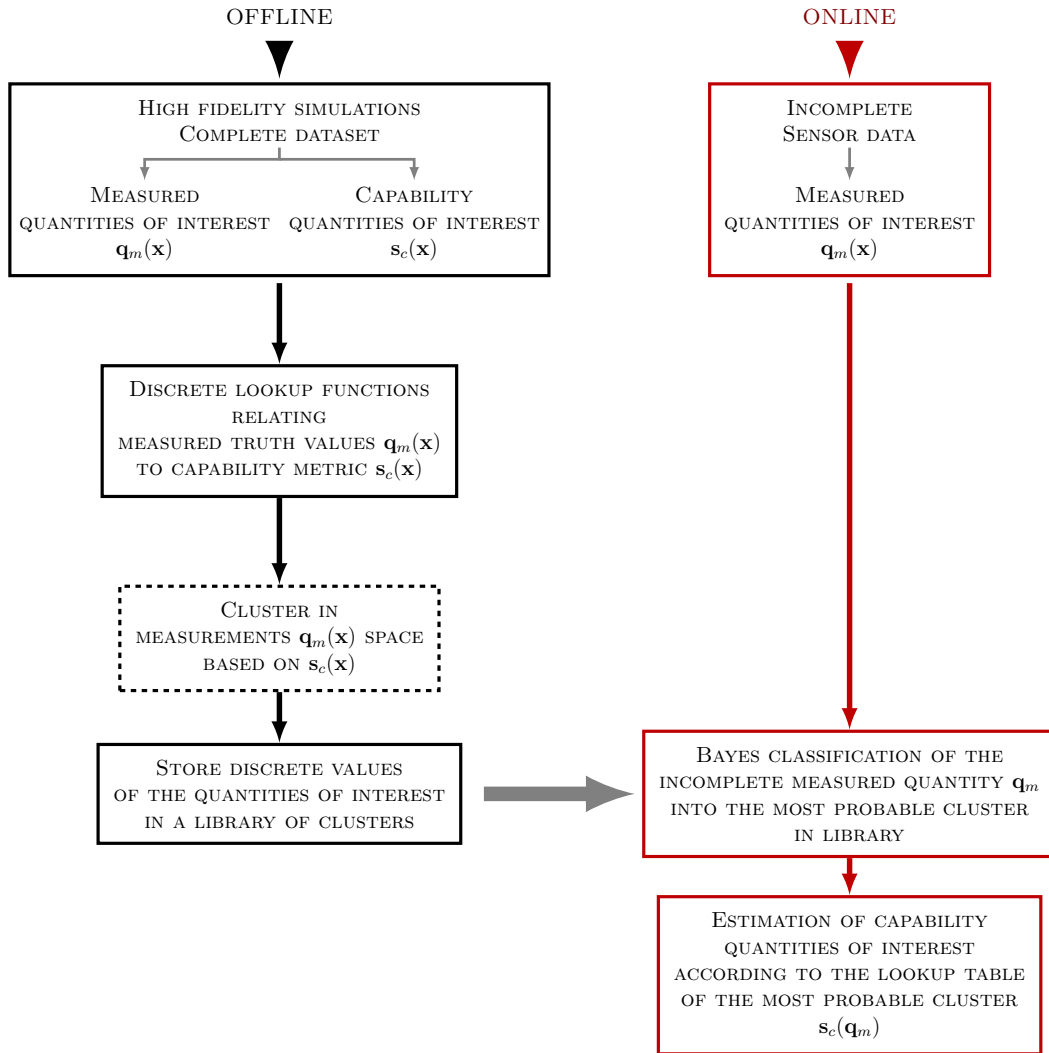


Figure 6: Diagram of the offline (black boxes) and online (red boxes) steps of our approach at the vehicle level. Damage library information is stored using offline clustering based on the capability quantities of interest. The library information is employed online using a Bayes classifier as indicated by the gray arrow.

Figure 8 shows the corresponding online estimate of the failure index given by our surrogate modeling approach, reconstructed using strain sensor measurements that cover 50% of ply 4. The other two plots in Figure 8 are included to give insight to the errors due to the POD approximation and the self-organizing map as follows. The top right plot represents the best approximation of the original finite element solution in the POD basis—this would be achieved only if we could reconstruct the POD modal coefficients exactly. The bottom left plot shows that a small amount of additional error is introduced by using the self-organizing map to map from POD measurement coefficients to POD capability coefficients. The final plot in the lower

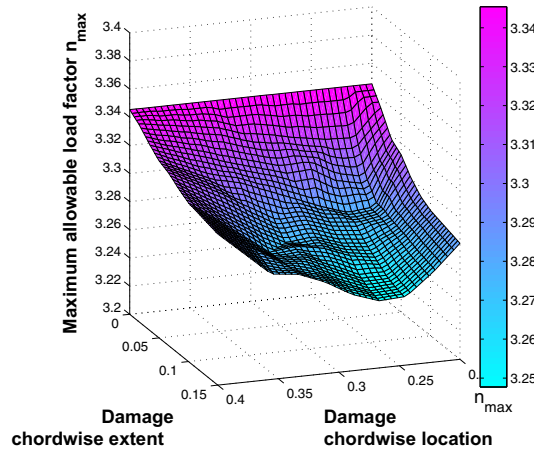


Figure 7: Surface representing the vehicle capability as a function of two damage parameters using the offline vehicle model. A pull-up maneuver with constant velocity V and varying load factor n produces wing loading cases that are classified as safe or unsafe, producing a maximum safe load factor n_{max} for each damage case using a bisection algorithm. Note that when the chordwise damage extent is zero, the damage region is degenerate with zero volume, and the model operates using the baseline “pristine” aircraft configuration; hence, we see no change to the maximum allowable load factor.

right also includes the error due to inferring the POD measurement coefficients from sparse data. Overall, the reconstructions of the failure indices are sufficient to provide a first-cut assessment for online decision-making.

4 Conclusions

DDDAS methods and algorithms have significant potential to bring new capabilities to the design and operation of future aerospace vehicles. A self-aware vehicle is one example of achieving this through a synergistic combination of simulations and measurements, integrated dynamically in real time and feeding back to drive decision-making and adapt vehicle behavior. Our work is developing DDDAS methods that exploit an offline/online decomposition of tasks to incorporate information from multiple modeling sources and multiple sensors. We draw on techniques from reduced-order modeling, inference and uncertainty quantification, and combine them with physics-based models of the vehicle at multiple levels of resolution. Here we described the specific consideration of models at the local panel level and at the overall vehicle level. Ongoing work aims to quantify the benefits of the DDDAS-enabled vehicle relative to a vehicle designed using current practices.

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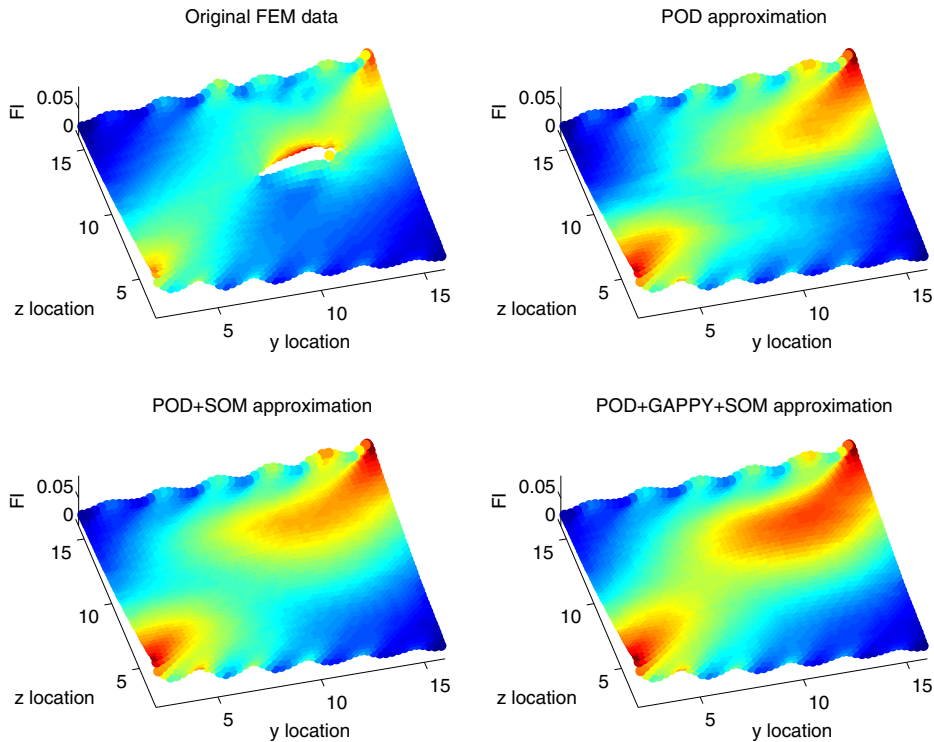


Figure 8: Failure index FI over the panel. The panel border containing the bolt holes is excluded for plotting clarity. Top left: the “truth” finite element model (FEM) solution. Top right: the representation of the FEM solution in the POD basis. Bottom left: POD approximation combined with self-organizing map (SOM) surrogate, mapping measurement POD coefficients to capability POD coefficients. Bottom right: our full approach using gappy POD to infer POD coefficients from measured data, and SOM to map from measurement POD coefficients to capability POD coefficients.

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